Super Resolution Techniques for Medical Image Processing

Jithin Saji Isaac
Department of Electronics & Telecommunication,
Vivekanand Education Society's Institute of Technology,
Chembur, Mumbai
jithinsaji@gmail.com

Dr. Ramesh Kulkarni
Department of Electronics & Telecommunication,
Vivekanand Education Society's Institute of Technology,
Chembur, Mumbai
ramesh.kulkarni@ves.ac.in

***Abstract*— Images with high resolution are desirable in many applications such as medical imaging, video surveillance, astronomy etc. In medical imaging, images are obtained for medical investigative purposes and for providing information about the anatomy, the physiologic and metabolic activities of the volume below the skin. Medical imaging is an important diagnosis instrument to determine the presence of certain diseases. Therefore increasing the image resolution should significantly improve the diagnosis ability for corrective treatment. Furthermore, a better resolution may substantially improve automatic detection and image segmentation results. The arrival of digital medical imaging technologies such as Computerized Tomography (CT), Positron Emission Tomography (PET), Magnetic Resonance Imaging (MRI) etc. has revolutionized modern medicine. Despite the advances in acquisition technology and the performance of optimized reconstruction algorithms over the two last decades, it is not easy to obtain an image at a desired resolution due to imaging environments, the limitations of physical imaging systems as well as quality-limiting factors such as Noise and Blur. A solution to this problem is the use of Super Resolution (SR) techniques which can be used for processing of such images. Various methods have been described over the years to generate and form algorithms which can be used for building on this concept of Super resolution. This paper details few of the types of medical imaginary, various techniques used to perform super resolution and the current trends which are being followed for the implementation of this concept.**

***Keywords*— super resolution; medical images; MRI; CT**

I. Introduction

Digital image processing deals with the manipulation of digital images with the help of a digital computer. It is the process of converting an image into the digital form and subsequently performing some operations on it. The final aim is to get an enhanced image or to extract some useful information from a region of interest in it. Image Processing forms core research area within engineering and computer science disciplines too. Digital processing techniques help in the manipulation of the obtained digital images since raw data from imaging sensors in various platforms contains deficiencies. Such images have to undergo sustained processing such as to get over the abnormalities and to help obtain the original information. The three phases that all types of image data have to undergo while using digital image enhancement techniques are Pre-Processing, Enhancement and Information extraction.

In almost every application, it is desirable to obtain an image that has a very high resolution. A high resolution image will lead to a better classification of regions in an image or help to obtain a higher degree of accuracy in the localization of a tumor in a medical image or could lead to a more high level of user satisfaction while watching high definition videos on high definition televisions (HDTV) or web-based images. The resolution of an image is generally directly related to the resolution of the image acquisition device. However, as the resolution of the image generated by a sensor increases, so does the cost of the sensor and hence it may not be an affordable solution. Therefore the important point to understand is if there is any way of increasing the resolution of the image. This review paper details the concept of Super resolution and how it is used for Medical image processing.

II. The Concept of Super Resolution

The goal of Super Resolution (SR) or Super Resolution Reconstruction (SRR) methods is to recover a High Resolution (HR) image from one or more Low Resolution (LR) input images. Super Resolution (SR) is done using additional information such as multiple low-resolution images or a database that learns relationship between low and high-resolution images. There are numerous applications of super-resolution in the areas of image processing and computer vision such as target detection, recognition, tracking etc. Modern television receiver uses picture memory for up-sampling and decoding processes. This technique allows the recovery of a high-resolution image from several low-resolution images. These LR images are noisy, blurred and down-sampled.

The basic idea of Super-resolution is that a combination of low resolution or noisy sequence of images of a scene can be effectively used to generate a high resolution image or image sequence. The general approach considers the low resolution images as resulting from re sampling of a high resolution image. The final step is to recover the high resolution image. When this high resolution image is resampled based on the input images and the imaging model, it will produce the low resolution observed images. Most of the super-resolution

978-1-4799-8187-8/15/$31.00 ©2015 IEEE

image reconstruction methods consist of three basic components; Motion compensation, Interpolation and blur-noise removal. Motion compensation is used to map the motion from all available low resolution frames to a common reference frame. Interpolation refers to mapping the motion-compensated pixels onto a super-resolution grid. Blur and noise removal is needed to remove the sensor and optical blurring. These techniques classify Super Resolution into two categories: Single image Super Resolution and Super Resolution from several frames i.e. Multiple Image Super Resolution.

The single-image SR methods, also known as example learning- based methods have emerged as an efficient solution to the spatial resolution enhancement problem [1]. An advantage of these methods is that they do not require many LR images of the same scene as well as registration. In these methods, an image is considered as a set of image patches and SR is performed on each patch. The focus of single-image super resolution is to estimate a high-resolution (HR) image with just a single low-resolution image and the missing high frequency details are recovered based on learning the mapping between low and high-resolution images.

III. TYPES OF MEDICAL IMAGES

Medical imaging is the process of creating visual representations of the interior organs of the human body for clinical analysis and effective medical intervention and supervision. Medical imaging is used to make visible internal structures and problems hidden by the layer of skin and bones, thereby helping in proper diagnosis and treatment.

The Medical practitioner who is entrusted the duty of interpreting the medical images is a Radiologist. Despite the advances in acquisition technology and the performance of optimized reconstruction algorithms over the two last decades, it is not easy to obtain an image at a desired resolution due to imaging environments, the limitations of physical imaging systems as well as due to factors such as noise and blur.

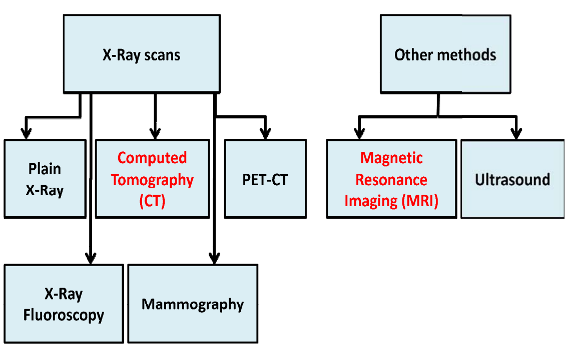


Fig. 1 Different types of Medical Images

Few of the different types of Medical imaging techniques can be stated as follows:

A. *X-ray Computed Tomography (X-Ray CT)*

It is a technology that uses computer-processed X-Rays to produce tomographic three dimensional images (virtual slices) of specific areas of the scanned object, allowing the radiologist to see inside without cutting.

B. *Positron Emission Tomography/Computed Tomography (PET-CT)*

Positron Emission Tomography/Computed Tomography is a diagnostic tool used in oncology staging and for planning surgery and treatment. PET/CT combines two scanning techniques: positron emission tomography (PET) and computerized tomography (CT). The CT scanner takes a series of two-dimensional cross-section images (‘slices’) around an axis. A three-dimensional image is then constructed using computer processing.

C. *Magnetic resonance imaging (MRI)*

Magnetic Resonance Imaging instrument (MRI scanner) or “Nuclear magnetic resonance (NMR) imaging” is a powerful diagnostic tool that uses a strong magnetic field to produce high-quality images in multiple planes or directions.

IV. SUPER RESOLUTION IN MEDICAL IMAGES

The following Section A gives a brief about the basic difference between Interpolation & Super Resolution concepts. Also, various difficulties are encountered when medical images are processed. The difficult aspects of medical image processing are detailed in the part B of this section.

A. *Difference between Interpolation & Super Resolution*

Enhancing spatial resolution i.e. Interpolation is an alternative solution to improving resolution i.e. to detect and discriminate the smallest possible details that can be seen. The task of enhancing the spatial resolution while effectively reducing noise is a challenging problem in medical imaging especially when the images are severely corrupted by noise. The conventional and well-known interpolation techniques for enhancing image resolution are unfortunately inefficient when the given low-resolution image is corrupted by noise. Moreover, these techniques may also introduce blurring, ringing, as well as aliasing artifacts. The presence of high-frequency components in the image, such as edges and texture details, are not taken into consideration, resulting in blurring as well as appearance of unpleasant “jaggy” artifacts.

Here, Super Resolution comes into account. Super-resolution (SR) consists of using additional information such as multiple low-resolution (LR) images or a database that learns relationship between low and high-resolution images. Both these techniques are interlinked and required for proper diagnosis of the region of interest.

B. *Problems with existing systems in Medical Image Processing*

As the number of images to be inspected increases, the role of medical specialists becomes extremely time consuming and exhausting. For instance, assuming a wireless capsule endoscope takes two images per second during two hours of traveling through the small intestine, the total number of captured images exceeds 50,000. The captured images suffer from various degradations, due to undesired noises, such as thermal ones in CCD/CMOS chips, and hence their image quality is too degraded. Apart from CCD/CMOS thermal noises, some of the major causes of dissatisfactory quality in endoscopic images are inhomogeneous brightness and poor contrast, which are unavoidable due to the convoluting, bending and waving nature of the gastric organs. Medical images generally have the following problems:

- Low resolution (in the spatial and frequency domains)
- High level of noise
- Low contrast images
- Geometric deformations
- Presence of imaging artefacts

V. CURRENT TRENDS IN MEDICAL IMAGE PROCESSING

A. Dynamic Range Enhancement of MRI Images

There are a lot of problems of inhomogeneous brightness and poor contrast in medical images. Adaptive image enhancement techniques are known to render better overall results but they come with a much higher computational cost.

The Retinex theory is based on observations about the color constancy concept of the human visual system. It decomposes a given image *I(x,y)* into two different images: the Reflectance image *R(x,y)* and the Illumination image *L(x,y)* as depicted in *Fig. 2*

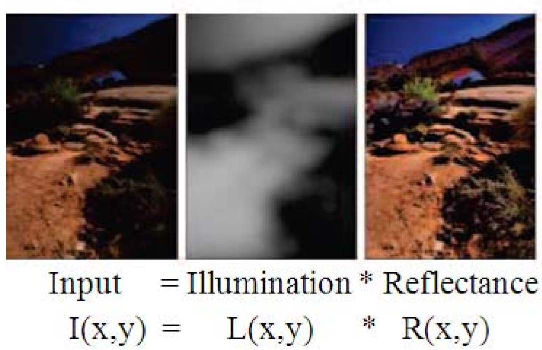


Fig. 2. Retinex Theory [3]

Color constancy phenomenon means that the human visual system can practically recognize and match colors under a wide range of different illuminations. The Retinex theory utilizes this property to extract the illumination image. Hence, image enhancement can be achieved first by estimating the Illumination image *L(x,y)* from the input image *I(x,y)* and then by calculating the Reflectance image *R(x,y)*. This is the illumination-independent image. Among the different illumination models proposed for the Retinex theory, the variational model as the most viable for practical applications in terms of computational cost and image quality is used.

A Projected Normalized Steepest Descent (PNSD) algorithm is used. When this scheme has been implemented, it has been experimentally observed that omission of the Illumination estimation for high resolution layers contributes to a huge reduction of cost and hardware implementation area, and with only marginal degradation of the processed image quality.

The block diagram of the architecture is shown in Fig. 3. The architecture consists of three stages; (1) Down sampling and color space conversion, (2) Illumination estimation, and (3) Image enhancement.

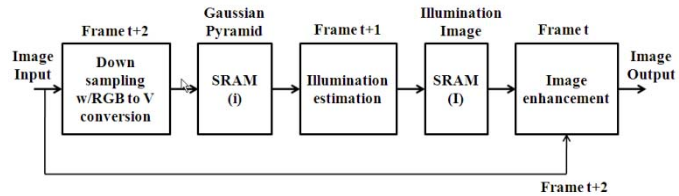
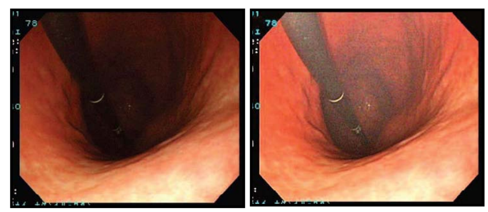


Fig. 3. Block diagram of architecture [3]



(a) (b)

Fig. 4. (a) Endoscopic Image of stomach without dynamic range enhancement and
(b) Endoscopic Image of stomach with dynamic range enhancement [3]

Fig. 4 compares an image for a body of the stomach. In the image Fig. 4. (a), the tube of the endoscope in the dark inner part cannot be discerned. But after dynamic-range enhancement the shape of the tube becomes visible in the originally dark inner part of the stomach.

A detailed description of the Super Resolution scaling algorithm [3] is presented in the following Fig. 5

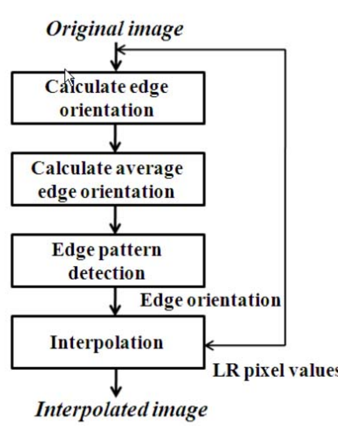


Fig. 5. Super Resolution Scaling algorithm [3]

In the step 1, the edge orientation is calculated which indicates the contrast between adjacent pixel values within each block of pixels in the image.

In step 2, the average of the edge orientation metrics of blocks in the neighborhood of each block is calculated.

In step 3, the edge orientation in the region centered on each block is computed.

In step 4, calculation of the high resolution pixel through interpolation is done.

When we compare the quality of the HR image scaled up using Bicubic and Lanczos interpolation, it has been observed that the image quality attained is on the average superior in the given super Resolution algorithm which is measured by the SSIM metric. Bicubic interpolation is subject to blurring whereas the Bilinear interpolation is affected by "jaggy" artifact. The super resolution algorithm given is capable of rendering sharp edges without visible artifacts.

B. *Denoisiong, Learning based example database and Patch Super Resolution method for MRI & CT images*

The main aim of single-image super resolution is to estimate a high-resolution (HR) image with just a single low-resolution image and the missing high frequency details present are recovered based on learning the mapping between low and high-resolution (HR) image patches from a database constructed from examples. There have been a large number of learning-based methods. These have demonstrated promising results. Some methods are based on nearest neighbor search. Here, each patch of the LR image is compared to the LR patches stored in the database in order to extract the nearest LR patches and hence the corresponding HR patches. These HR patches are then used to estimate the output. After finding the nearest LR neighbors such that it is closest to a given input LR patch, the output HR patch is estimated by replacing LR patches with the associated HR patches in the linear combination. The drawback of these methods is that they highly depend on the number of nearest neighbors [8]. One of the issues of the example-based super-resolution is that it depends to a great extend on the database of low and high-resolution image patch pairs. The example-learning-based super-resolution algorithms assume that the input images are free of noise. However such an assumption is not true for medical images. Denoising and then Super Resolution are used to deal with such problems. However, these methods only deal with a small amount of noise where artifacts are created in the denoising step and magnified in the super resolution step.

So the main aim is to design a novel example-based SR method for medical images which are inherently corrupted by noise. By combining denoising and super-resolution in the same setup, this can be achieved. The main limitation of these methods is that the main effectiveness of this method highly depends on the supporting database of example images. But we see that many images are acquired at approximately the same location. Thus, we can collect similar (same organ and same modality) and reasonable good quality (proven by experts) images and use them as examples to establish a database of low and high resolution image patch pairs. We refer such images as standard images with respect to an input LR image. By using a given set of example images, this method is performed in a patch-wise manner. For an input LR image, a given set of standard images is used to construct a database of example high/low-resolution image patch pairs. This database will be used for the patch SR before the entire HR reconstruction.

Experimental results in [2] show that this method yields excellent SR results as well as effectively removes noise. It is referred to as *SRSW (Super-Resolution by Sparse Weight).*

Thus, this Super Resolution model consists of two main steps as follows: Patch super-resolution and then reconstruction of the entire HR image which allows aggregating the final HR image using the estimated HR patches in the first step.

The experimental tests are performed on five 8-bit images used as test HR images and shown in Fig. 6.

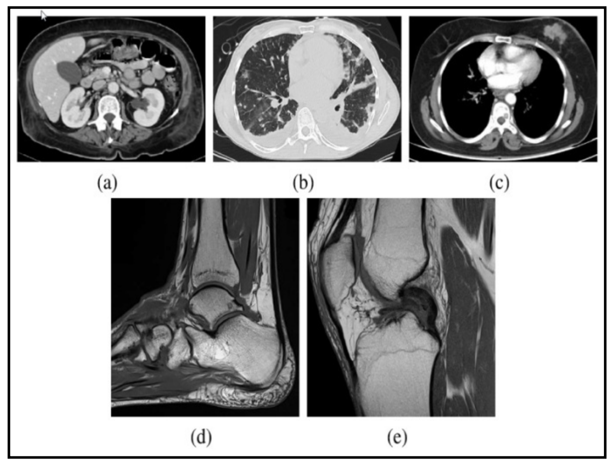


Fig. 6. HR test images: CT of abdomen (a), CT of thorax (b), CT of chest (c), MRI of ankle (d), and MRI of knee (e). [2]

The training databases of all the methods are established with the same set of five standard images as illustrated in Fig. 7

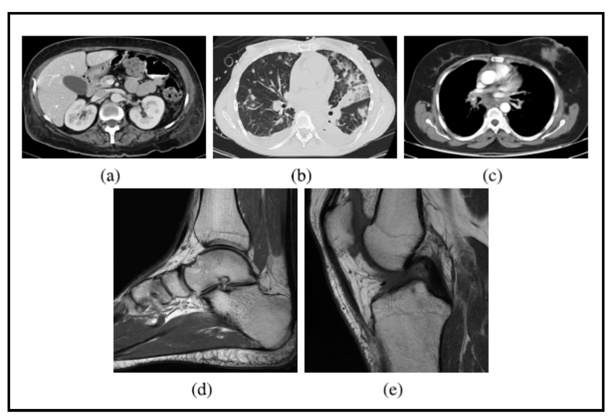


Fig. 7. Standard images used to construct database: CT of abdomen (a), CT of thorax (b), CT of chest (c), MRI of ankle (d), and MRI of knee (e). [2]

For each test image in Fig. 6, a corresponding standard image in Fig. 7 is used as example. In all experiments done in [2], the LR image is created from the corresponding test image in three steps: First, the test image is blurred by a 7 × 7 Gaussian filter with standard deviation 1, then down sampling by decimation factor of s is performed, and finally the Gaussian white noise with standard deviation σ is added into the decimated image. The experiments are conducted in both noise-free image ($\sigma = 0$) and noisy image ($\sigma = 5$, 10 and 20).

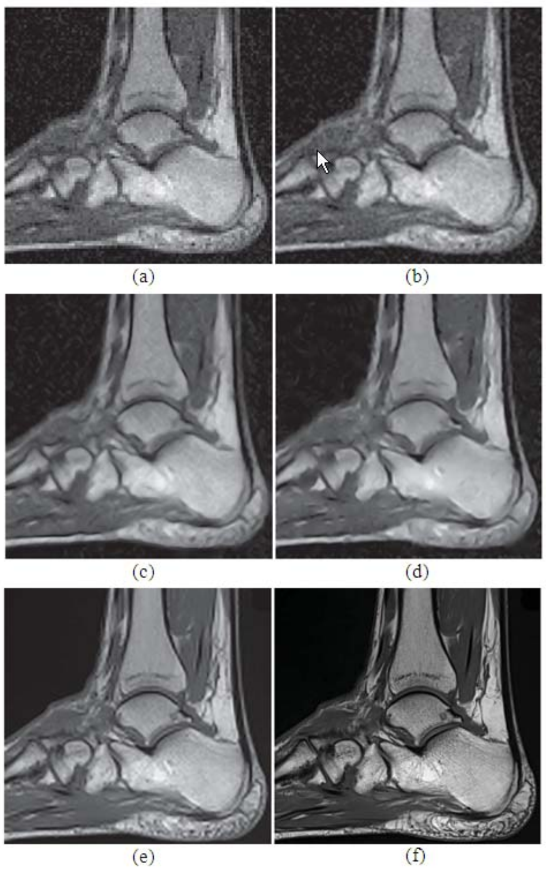


Fig. 8. Magnification results (4x) of MRI image of ankle for various combinations with noise level $\sigma = 10$
(a) LR image (size 100 × 100) corrupted by Gaussian noise with $\sigma = 10$ (shown with nearest neighbor interpolation). (b) Result of the bicubic interpolation (PSNR = 22.63 dB, SSIM = 0.56). (c) Result of the NE method with the number of neighbors $K = 10$ (PSNR = 23.34 dB, SSIM = 0.58). (d) Result of the ScSR method [30] with the regularization parameter λ=0.8, (PSNR = 23.87dB, SSIM = 0.62). (e) Result of the SRSW method (PSNR = 25.40 dB, SSIM = 0.75). (f) Original test image. [2]

This algorithm [2] is very robust to heavy noise. The method depends on using of standard, good quality images so as to enhance the spatial resolution while de noising the given degraded and low-resolution image.

C. *High Resolution Image from Two Orthogonal Low Resolution Data Sets*

Magnetic resonance and computed tomography images often suffer from anisotropic resolution. As a result the image quality is high only within the slices. This part of the report [5] explains to reconstruct isotropic high resolution images from only two orthogonal low resolution data sets.

The majority of MRI and CT scanners acquire images with anisotropic voxels. The in-slice resolution is better than the out-of-slice resolution. To overcome this problem, super-resolution reconstruction (SRR) methods are introduced. Projection onto convex sets (POCS) algorithm is one method [5]. It defines convex sets and presents tight constraints on the HR image, and combines it within the restoration step. Non-consideration of the fidelity of the input data is one major drawback. Thus reconstruction can fail in presence of homogeneity or metal artifacts. The scheme of presented reconstruction method in [5] allows simultaneous incorporation of regional and local information thus resulting in more robustness against noise.

This method aims to reconstruct the HR image and consists of the following steps: (1) Preprocessing to address the intensity differences and correct subject motion between input images and (2) Initial estimation of the HR image (3) Iterative reconstruction. [5]

In the method called as Confidence MAP (cMAP), during up sampling and registration, missing values are computed by interpolating neighboring voxels as sampling points. This method aims to reconstruct a 3D high resolution image from two orthogonal LR data sets. In practice the number of LR images is limited. Thus, the number of input sets is fixed to two. However it is possible to apply this approach to any number of input images.

The main contributions of this work are the estimation of input information uncertainty and the improved initial estimation of HR image. It is shown that the reconstruction quality can be improved by applying the cMAP method.

The ability of reconstruction HR MR Images for brain structures were explored by applying different SRR algorithms on T1, T2 and PD weighted MR images. A quantitative analysis is performed in term of signal to noise ratio.

TABLE I
COMPARING THE PSNR OF HR AND SR IMAGES FOR VARIOUS SIGNAL WEIGHTINGS (S.W) T1, T2 AND PD. DONE USING VARIOUS SRR TECHNIQUES I.E. AVG (AVERAGING), MAXIMUM A POSTERI (MAP) AND CMAP. [5]

	S.W.	**AVG**	**MAP**	**cMap**
PSNR [dB]	T1	24.23	30.20	30.40
PSNR [dB]	T2	18.39	22.14	22.97
PSNR [dB]	PD	20.24	24.79	25.27

VI. CONCULSION

Through the course of this report, we have come across the different types of medical images used in Medical image processing. It has been understood that resolution plays an important part in extraction of important information from the images. Better image resolution will help for accurate diagnosis of the ailment and will help in faster rate of treatment to the patients. But medical images typically consist of lot of noise and irregularities due to the anatomical structure of the human body and also due to the limitations of the image acquisition device sensors. Super Resolution technique has been detailed to be used to overcome this problem of resolution. By using effective super resolution algorithms, the resolution of low resolution medical images can be satisfactorily increased to required levels. Different methods have been detailed for enhancing the resolution via Super resolution.

Dealing with the pre processing part by dynamically enhancing the resolution, de noising the medical images and later on to apply Super resolution techniques of Example based, patch based and orthogonal acquisition algorithms have been explained in the report. There is tremendous future scope in this method of applying SR techniques for medical image processing. Enhancing the present algorithms such as to increase the PSNR and SSIM values can be formulated which gives better results as compared to the ideas discussed in this report.

REFERENCES

[1] S. Chaudhari, Department of Electrical Engineering, Indian Institute of Technology – Bombay, Mumbai, India 400 076, “Super Resolution Imaging”. New York, Boston, Dordrecht, London, Moscow, Kluwer Academic Publishers.

[2] D. Trinh, M. Luong, F. Dibos, J. M. Rocchisani, C. D. Pham and T. Q. Nguyen, “Novel Example-Based Method for Super-Resolution and Denoising of Medical Images”, IEEE Transactions on Image processing, Vol. 23, No. 4, April 2014.

[3] H. Okuhata, R. Imai, M. Ise, R. Y. Omaki1, H. Nakamura, S. Hara and I. Shirakawa, “Implementation of Dynamic-Range Enhancement and Super-Resolution Algorithms for Medical Image Processing” in 2014 IEEE International Conference on Consumer Electronics (ICCE).

[4] F. Rousseau, D. Gounot and C. Studholme, “On High-Resolution Image Estimation using Low-Resolution Brain MRI”, 35th Annual International Conference of the IEEE EMBS, Osaka, Japan, 3 - 7 July, 2013.

[5] W. E. Hakimi and S. Wesarg, “Accurate Super-Resolution Reconstruction for CT and MR Images”.

[6] R. Islam, A. J. Lambert and M. R. Pickering, “Super Resolution of 3D MRI Images Using A Gaussian Scale Mixture Model Constraint”, 978-1-4673-0046-9/12/$26.00 ©2012 IEEE.

[7] D. Glasner, S. Bagon and M. Irani, “Super-Resolution from a Single Image”, IEEE 12th International Conference on Computer Vision (ICCV), 2009.

[8] A. Ozcelikkale, G. B. Akar, H. M. Ozaktas, “Accurate Super-Resolution Reconstruction for CT and MR Images”, IEEE 17th International Conference on Image Processing, September 26-29, 2010, Hong Kong.

[9] A. Souza and R. Senn, “Model-Based Super-Resolution for MRI”, 30th Annual International IEEE EMBS Conference, Vancouver, British Columbia, Canada, August 20-24, 2008.